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Mapping the Spatial Variability of Groundwater Quality in Urmia, Iran

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Abstract: Groundwater deterioration hazard assessments are needed for clearer appreciation of the actions needed to protect groundwater quality, and should become an essential component of environmental best-practice. Water quality mapping is the main procedure of this assessment. At present research, we compare efficiency of three interpolation techniques included inverse distance weighting, kriging and cokriging for predicting of some groundwater quality indices such as: Na^+, TH, EC, SAR, Cl^- and SO_4^{2-}. Data were related to 97 wells in Urmia plain, Azarbayjan Province, Iran. After normalization of data, variogram was computed. Suitable model for fitness on experimental variogram was selected based on less root sum of square value. Then the best method for interpolation was selected, using cross-validation, mean error and root mean square error. Results showed that for SO_4^{2-} kriging had the lowest root mean square error and for SAR co-kriging performed better than other methods and for the rest of groundwater quality indices included TH, EC and Cl^- and Na^+, inverse distance weighting technique had better result than geostatistical method to simulate groundwater quality indices. Finally, using geostatistical and inverse distance weighting methods, map of Groundwater were prepared in GIS environment.

Key words: Groundwater quality, Interpolation, Geostatistics, Urmia plain

Introduction

Groundwater is a vital natural resource for the reliable and economic provision of potable water supply in both the urban and rural environment. It thus plays a fundamental (but often little appreciated) role in human well-being, as well as that of some aquatic and terrestrial ecosystems. Worldwide, aquifers (geological formations containing usable groundwater resources) are experiencing an increasing threat of pollution from urbanization, industrial development, agricultural activities and mining enterprises [9]. Thus practical actions to protect the natural quality of groundwater are widely required. Water resources planning and management provides decision-tools for: (a) allocation of adequate water to the consumers at appropriate time and place; (b) protection from excessive water (e.g. floodwater); and (c) maintenance of acceptable water quality [14]. The increase in water demand with population growth is applying more stress on available water resources and calls for an efficient and acceptable management of the resources [9]. Groundwater quality mapping over extensive areas is the first step in water resources planning [21].

In mapping Groundwater quality, two main stages can be distinguished: 1) the sampling stage, during which measurements are taken of the environmental variable at selected locations; and 2) the prediction stage, during which the observations are interpolated to a fine grid. The quality of the resulting map is determined by both stages. Geostatisticians and pedometricians have concentrated most on the second stage, by applying various types of interpolation methods [11, 22]. Geostatistical methods were developed to create mathematical models of spatial correlation structures with a variogram as the quantitative measure of spatial correlation. The variogram is commonly used in geostatistics and the interpolation technique, known as kriging, provides the ‘‘best’’, unbiased, linear estimate of a regionalized variable in an un-sampled location, where ‘‘best’’ is defined in a least-squares sense. The emphasis is set on local accuracy, i.e. closeness of the estimate to the actual, but unknown, value without any regard for the global statistical properties of the estimates. The kriging estimation variances are independent of the value being estimated and are related only to the spatial arrangement of the sample data and to the model variogram [22]. In recent years, many scientists have evaluated accuracy of different spatial interpolation methods for prediction of groundwater quality parameters. Nazari et al. [15] used geostatistics method to study spatial variability of Groundwater quality in Balarood plain. Their results showed that spherical model is the best model for fitting on experimental variograme of EC, Cl^- and SO_4^{2-} variables. Istock and Cooper [12] used kriging method to estimate heavy metals concentration in Groundwater and concluded that the mentioned method is the best estimator for spatial prediction of Lead. Dagostino et al. [5] studied spatial and temporal variability of Groundwater nitrate, using kriging and cokriging methods. Their results showed that cokriging method has higher accuracy than kriging in estimating of nitrate concentration. Rizzo and Mouser [16] used geostatistics for analyzing Groundwater quality. They used microbial data as an auxiliary variable in cokriging method. Their results showed that cokriging method has suitable accuracy to estimate Groundwater quality. Ahmad [1] found that kriging method has a high accuracy in estimating of TDS in Groundwater. Gaus et al. [10] studied Groundwater pollution in Bangladesh. They used disjunctive kriging method to estimate Arsenic concentration and to prepare risk map. Their results showed that 35 million people are exposed in high concentration of Arsenic (50ppm). Finke et al. [8] used simple kriging to estimate water surface changes in Netherlands and introduced it as a suitable method for mapping of water surface. Barca and Passarella [3] used Disjunctive kriging and simulation methods to make nitrate risk map in 10, 50 (mgr/lit) thresholds, in Modena plain of Italy. Their results showed that Disjunctive kriging method is the suitable method to study deterioration level of Groundwater. Because of various results reported by above mentioned researchers, it is obvious that suitable method of interpolation to estimate one variable depends on variable type and regional factors, thus any selected method for specific region cannot be generalized to others.

The present study was therefore, carried out with objectives to evaluate accuracy of different interpolation methods, kriging, cokriging and IDW, for prediction of some Groundwater quality parameters in Urmia region.

Material and Methods

Study area

Urmia is the capital of West Azerbaijan province, in the Azerbaijan region of Iran. This region is located between the eastern longitude of (44◦, 20 and 45◦, 20) and northern latitude of (37◦, 05 and 38◦, 05). Groundwater resources in Urmia Plain are very important sources of water. The underground aquifer of this plain is a large natural collecting reservoir and regulator of water inflowing from the large drainage area, which both retains water and enables its useful utilization. Hydrological investigations have shown that this underground reservoir spreads under an area of approximately 529.8 km^2. Nazlu-Chai, Rowzeh-Chai, Shahr-Chai and Balanush- Chai are the four main rivers, which are flowing in the plain. They originate from the western mountainous area and end in Urmia Lake [2]. The location of study area and distribution of sampling points (data collected based in systematically method) is shown in Figure 1.

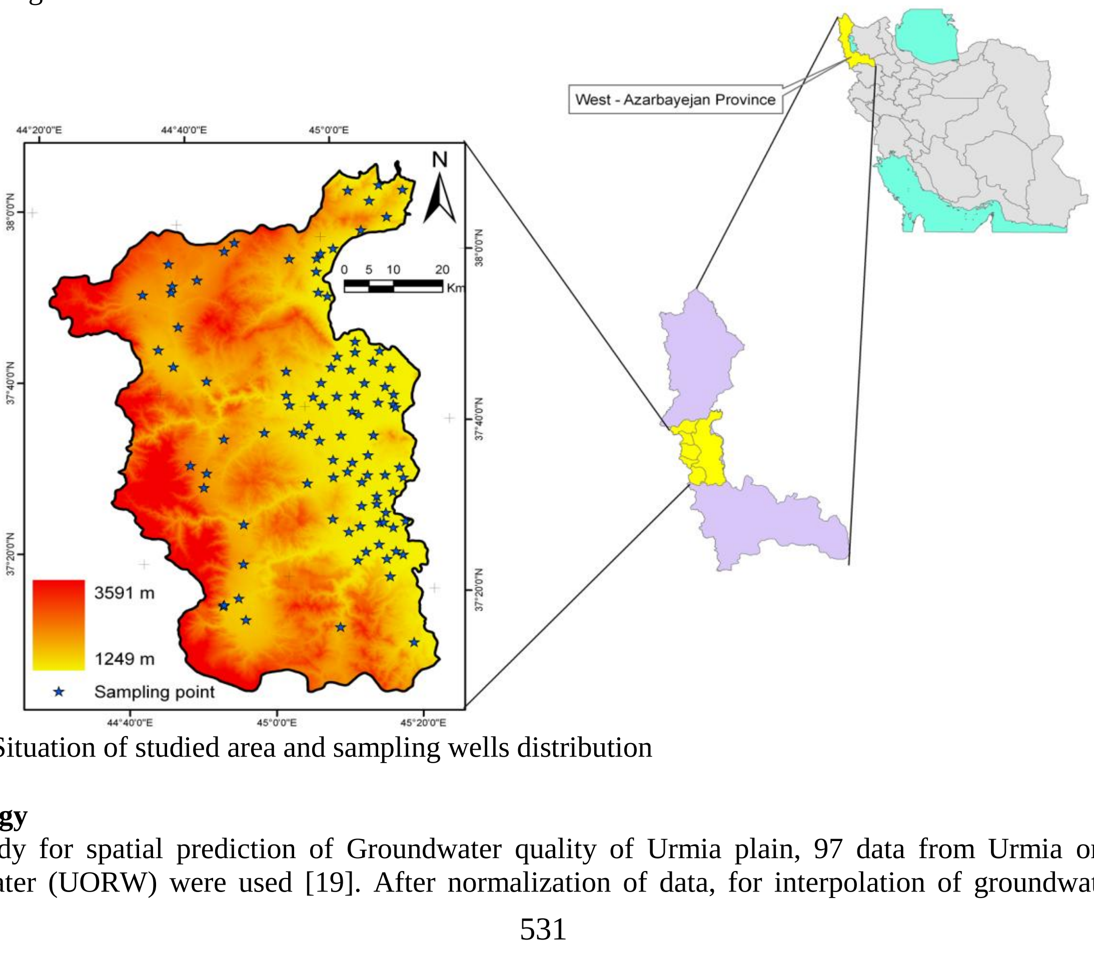

Figure 1. Situation of studied area and sampling wells distribution

Methodology

In this study for spatial prediction of Groundwater quality of Urmia plain, 97 data from Urmia organization regional water (UORW) were used [19]. After normalization of data, for interpolation of groundwater quality, kriging, cokrigong and IDW methods were used. Finally, with the use of cross-validation, the best method of interpolation was selected. We proceeded to prepare the map of groundwater quality based on this interpolation and the Geographical Information System (GIS). Figure 2 shows the flowchart of this study.

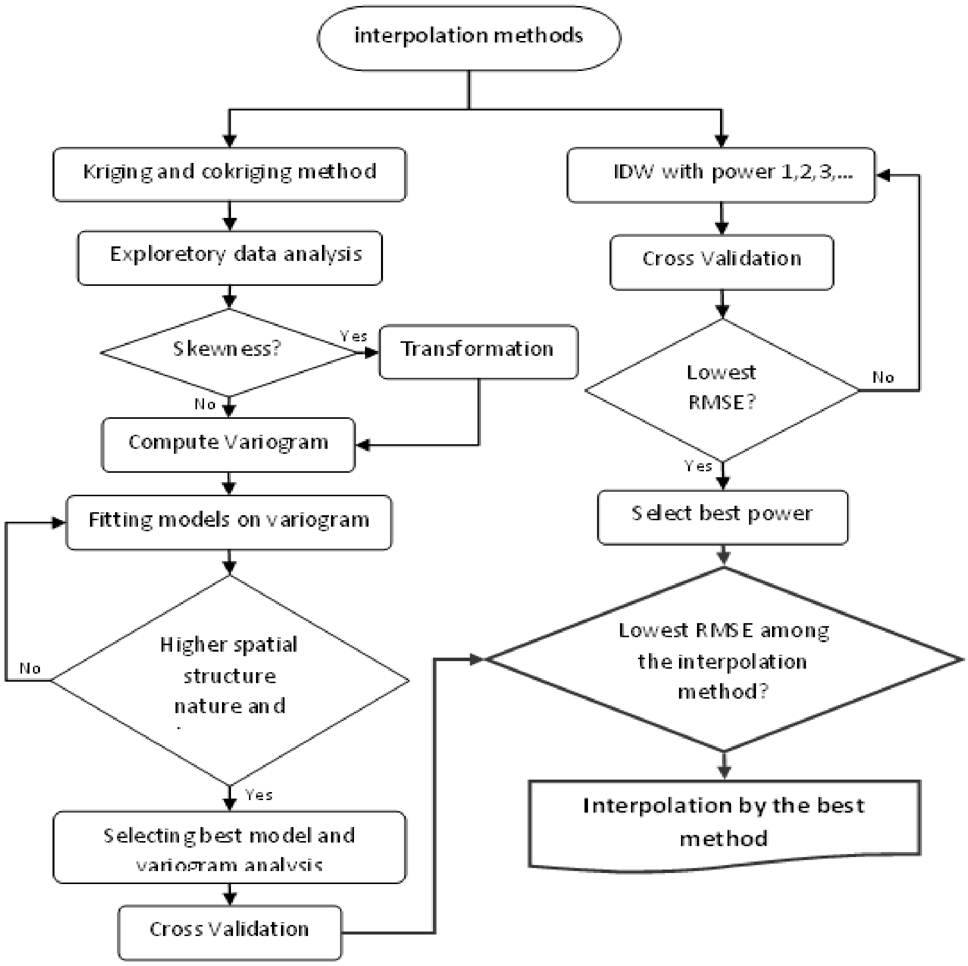

Figure 2. Flowchart of Geostatistic study and selection of the best model for estimation of variable

Spatial prediction methods

Kriging

The presence of a spatial structure where observations close to each other are more alike than those that are far apart (spatial autocorrelation) is a prerequisite to the application of geostatistics [11, 17]. The experimental variogram measures the average degree of dissimilarity between un-sampled values and a nearby data value [6,7], and thus can depict autocorrelation at various distances. The value of the experimental variogram for a separation distance of h (referred to as the lag) is half the average squared difference between the value at z (xi) and the value at z (xi + h) [13, 17]:

$$\gamma(h) = \frac{1}{2\mathrm{n}(\mathrm{h})} \sum_{i=1}^{n(h)} \left[Z(xi) - Z(xi + h) \right]^2 \qquad (1)$$

where n (h) is the number of data pairs within a given class of distance and direction. If the values at Z (xi) and Z (xi + h) are auto correlated the result of Eq. (1) will be small, relative to an uncorrelated pair of points. From analysis of the experimental variogram, a suitable model (e.g. spherical, exponential) is then fitted, usually by weighted least squares, and the parameters (e.g. range, nugget and sill) are then used in the kriging procedure.

IDW

In interpolation with IDW method, a weight is attributed to the point to be measured. The amount of this weight is depended to the distance of the point to another unknown point. These weights are controlled on the bases of power of ten. With increase of power of ten, the effect of the points that are farther diminishes. Lesser power distributes the weights more uniformly between neighbouring points. We should keep in mind that in this method the distance between the points count, so the points of equal distance have equal weights [4]. In this method the weight factor is calculated with the use of the following formula:

$$\lambda_i = \frac{D_i^{-\alpha}}{\sum_{i=1}^{n} D_i^{-\alpha}} \quad (2)$$

λ_i =the weight of point, D_i = The distance between point i and the unknown point, α = The power ten of weight

Cokriging

The “co-regionalization” (expressed as correlation) between two variables, i.e. the variable of interest, groundwater quality in this case, and another easily obtained and inexpensive variable, can be exploited to advantage for estimation purposes by the co-kriging technique. In this sense, the advantages of co-kriging are realized through reductions in costs or sampling effort. The cross-semivariogram is used to quantify cross-spatial auto-covariance between the original variable and the covariate [20]. The cross-semivariance is computed through the equation:

$$\lambda_{uv} h = \frac{1}{2} E\left[\{z_u(x) - z_u(x+h)\}\{z_v(x) - z_v(x+h)\}\right] \quad (3)$$

Where: $\gamma_{uv}(h)$ is cross-semivariance between u,v variable, $Z_u(x)$ is primary variable and $Z_v(x\ )$ is secondary variable.

Comparison between the different methods

Finally, we use the RMSE to evaluate model performances in cross-validation mode. The smallest RMSE indicate the most accurate predictions. The RMSE was derived according to Eqs. (4).

$$R.M.S.E = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (Z(x_i) - Z^*(x_i))^2} \quad (4)$$

Z(xi)* is observed value at point *xi* , *Z*(xi)* is predicted value at point *xi*, N is number of samples.

$$ME = \frac{1}{n} \sum_{i=1}^{n} \left[Z_{X_I} - Z^*{}_{X_i}\right] \quad (5)$$

Z(xi)* is observed value at point *xi*, *Z*(xi)* is predicted value at point *xi*, n is number of samples.

Results and Discussion

Many variables exhibit a non-normal distribution of measured values and therefore don’t initially satisfy the basic assumption of geostatistics of statistical normality. This restriction is eliminated, by applying a data transform to the sample values that make them more amenable to analysis and estimation. The most useful data transform is the log-transform. Since natural log values can be back transformed to real values, we can use a semi-variogram model derived from the transformed sample values to predict the spatial variation of logarithmic values of GWQI. A statistical summary of the groundwater quality properties is presented in Table 1. As shown in this table, all parameters had high skeness therefore they were normalized using logarithmic method.

Our task now is to fit models to the experimental or sample values choosing models and fitting them to data remain among the most controversial topics in geostatistic. There are still controversial who fit models by eye and who defined their practice with vigour. They may justify their attitude on the grounds that when kriging the resulting estimates are much the same for all reasonable models of the variogram. There are others who fit models numerically and automatically using “black box” software, often without any choice, judgment or control. This tool can have unfortunate consequences. We used a procedure that embodies both visual inspection and statistical fitting, as follow. First plot the experimental variogram. Then choose, from the models, one or more with approximately the right shape and with sufficient detail to achieve the principal trends in the experimental values. The best model for fitting on experimental variogram was selected based on less RSS value (Table 2).

Table 1. Results of statistical analysis on Groundwater quality

GWQI*	Min	Max	Mean	Std	Kurtosis	Skewness
TH(mg/L)	85	3000	383.557	388.149	24.06	4.61
TH(mg/L)**	4.44	8.01	5.748	0.541	4.46	1.55
SAR	0.1	6.9	1.0708	1.0819	8.62	2.46
SAR**	-2.3	1.94	-0.357	0.951	-0.71	-0.02
EC(µs/cm)	220	7550	919.38	1123.82	18.32	4.19
EC(µs/cm)**	5.39	8.93	6.54	0.62	3.85	1.64
SO_4^{2-}(meq/L)	0.5	7.8	1.92	1.4121	6.18	2.29
SO_4^{2-}(meq/L)**	-0.69	2.05	0.459	0.613	0.01	0.31
Cl^-(meq/L)	0.2	75	3.76	11.29	21.75	4.62
Cl^-(meq/L)**	-1.61	4.32	0.029	1.24	2.45	1.52
Na^+(mg/L)	0.2	25	2.34	3.68	18.84	4.04
Na^+(mg/L)**	-1.61	3.22	0.21	1.08	-0.19	0.32

**Ground Water Quality Indices; **Using logarithm to normalize data*

These variograms are showed in figure 3-8. Results showed that for Na^+, TH and SAR spherical model was selected as the best model. In this model, first, it has an almost linear increasing part, followed by a quite abrupt levelling of forwards the sill. However, for other parameters such as EC, Cl^- and SO_4^{-2} exponential model reaches the sill asymptotically, so there is no strict range.

Table 2. Selection of the most suitable model for evaluation on experimental variogram according to RSS

Models			GWQI
Guassian	Exponential	Spherical	
0.033	**0.0255**	0.034	EC
0.035	0.038	**0.028**	Na^+
0.181	**0.171**	0.267	Cl^-
0.024	**0.022**	0.031	SO_4^{2-}
0.009	0.007	**0.005**	TH
0.036	0.043	**0.034**	SAR

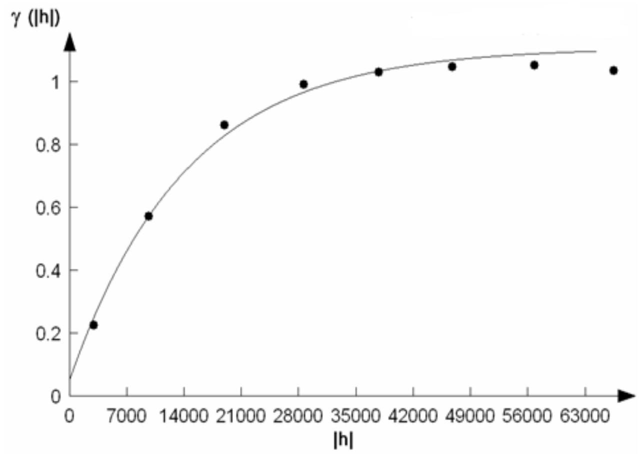

Figure 3 Variograms related to Groundwater quality (Cl^-)

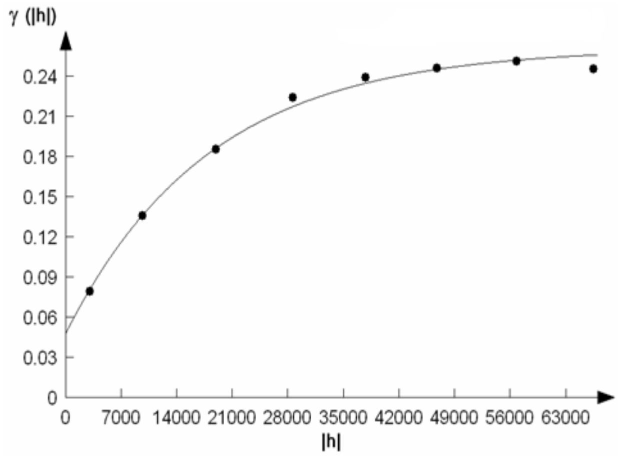

Figure 4 Variograms related to Groundwater quality (EC)

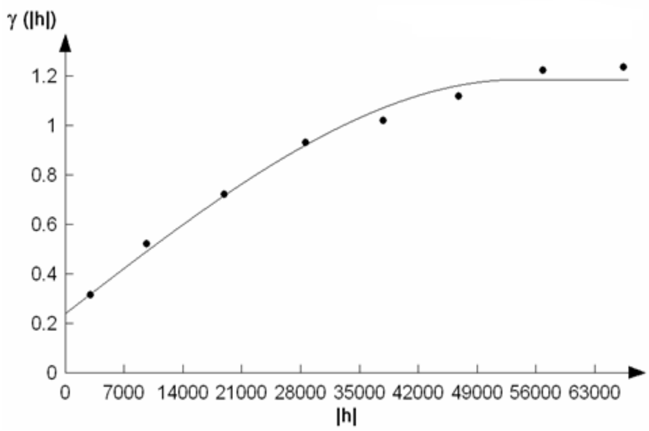

Fig. 5 Variograms related to Groundwater quality (Na^+)

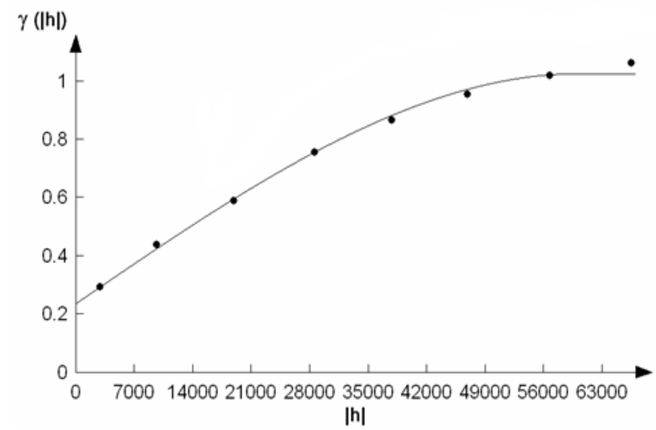

Fig. 6 Variograms related to Groundwater quality (SAR)

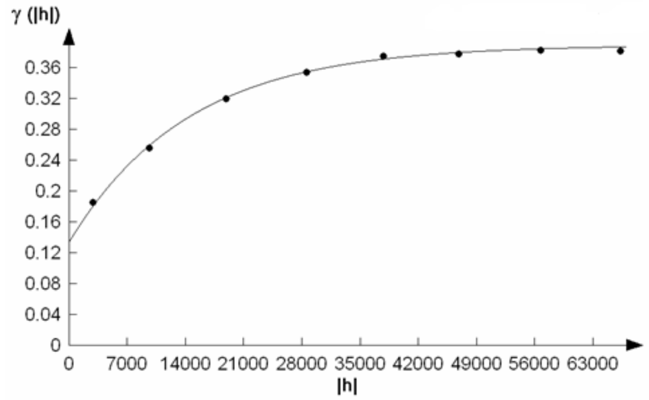

Fig. 7. Variograms related to Groundwater quality (SO_4^{2-})

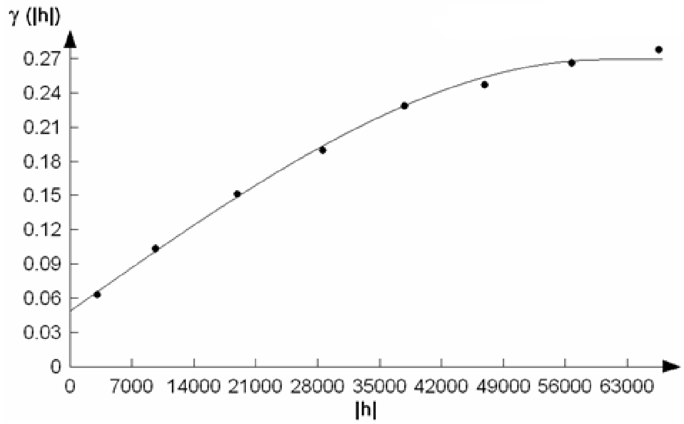

Fig. 8 Variograms related to Groundwater quality (TH)

Also, Table 3 illustrates parameters of Groundwater quality variograms. The ratio of nugget variance to sill expressed in percentages can be regarded as a criterion for classifying the spatial dependence of ground water quality parameters. If this ratio is less than 25%, then the variable has strong spatial dependence; if the ratio is between 25 and 75%, the variable has moderate spatial dependence; and greater than 75%, the variables shows only weak spatial dependence [18]. All parameters of ground water quality have strong spatial structure except SO_4^{2-}. Also effective range of most parameters is close together with the range of 42 to 60 Km. The effective distance demonstrates the distance that variogram has the highest value (Table 3).

Table 3. Best-fitted variogram models of ground water quality and their parameters

Groundwater quality	Model	Nugget(C_o)	Sill(C_O+C)	Range effect(Km)	(C_O/C_O+C) %
EC	Exponential	0.04	0.21	54.27	19
Na^+	Spherical	0.24	0.94	53.91	25
Cl^-	Exponential	0.05	1.05	42.73	4
SO_4^{2-}	Exponential	0.13	0.25	42.83	52
TH	Spherical	0.04	0.22	60.30	18
SAR	Spherical	0.23	0.78	60.16	29

First step for co-kriging is computing of cross-variograms. The cross-variogram can be modelled in the same way as that of variograms, and the same restricted set of functions is available. Having learned how to model the Cross-variograme, we can use our knowledge of the spatial relations between two variables to predict their values by cokriging. Typically the aim is to estimate just one variable, plus those of one or more other variable, which we regard as auxiliary variable. Cokriging reduces the estimations variance. By how much depend on the degree of under sampling. We used DEM as auxiliary variable to develop the cross-variograms. Cross variograms are presented in Figure 9-14.

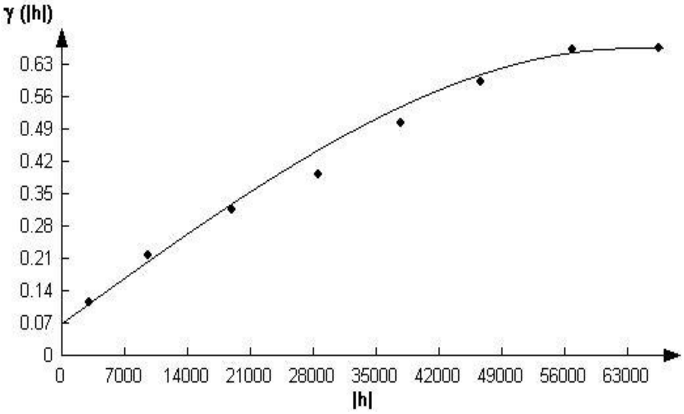

Fig. 9. Cross variogram of groundwater quality (Cl^--EC)

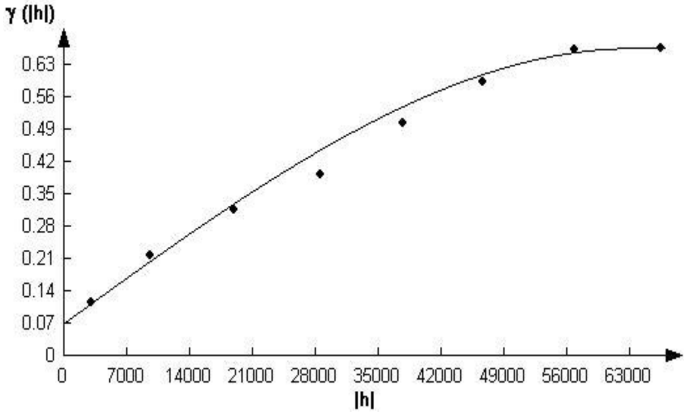

Fig. 10. Cross variogram of groundwater quality (Cl^--EC)

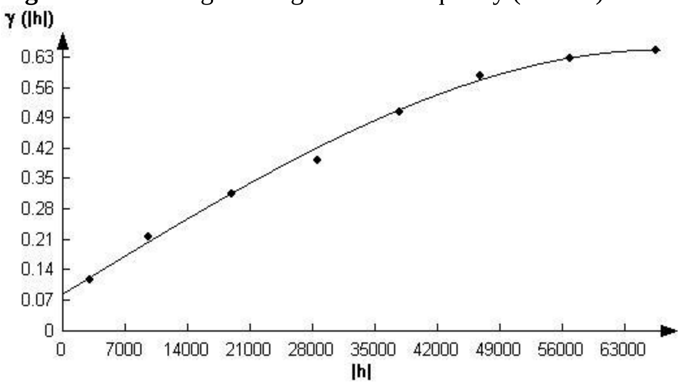

Fig. 11. Cross variogram of groundwater quality (EC-Cl^-)

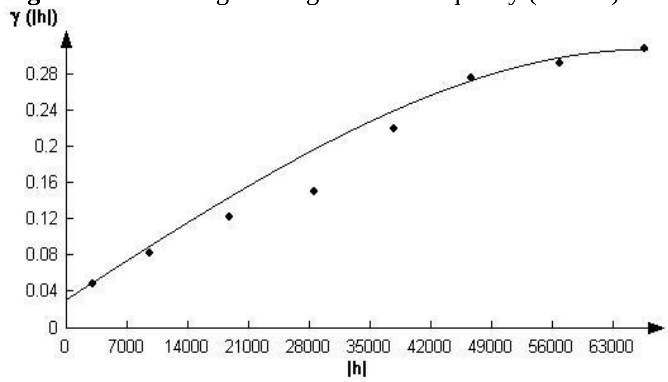

Fig. 12. Cross variogram of groundwater quality (SAR-Na^+)

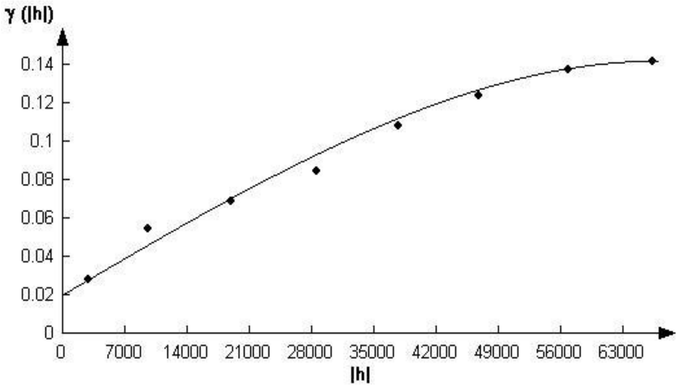

Fig. 13. Cross variogram of groundwater quality (SO_4^{2-}-SAR)

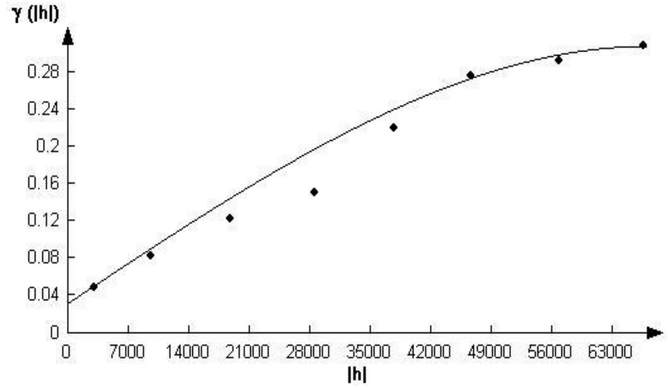

Fig. 14. Cross variogram of groundwater quality (Na^+-SAR)

For determination of the most suitable method, among Kriging, cokriging and IDW, RMSE and ME were used. Results showed that geostatistical methods had more considerable accuracy than IDW method for just two parameters included SAR and SO_4^{2-}. Otherwise, IDW showed higher accuracy than geostatistical method for prediction of Cl^-, EC, Na^+ and TH parameters (Table 4). Finally, maps of groundwater quality were prepared by cokriging and IDW which were the best methods for interpolation in GIS environment.

The analysis showed that for groundwater quality index, SO_4^{2-}, kriging performed better than cokriging and IDW techniques in characterizing the spatial variability and for SAR cokriging had better result than other methods which is in line with the work done by Rizzo and mouser [16]; Nazari et al. [15]; Ahmad [1]; Barca and Passarella [3]. They also revealed that geostatistical methods are the best model for interpolation. But we must careful about it. Geostatistic does obviously not offer a statistical model which is advantageous in every situation. Careful analysis of the measurement data using common sense can sometimes result in the same conclusions as those resulting from lengthily and computationally heavy calculations. In general, as spacing between samples is large compared to the dimensions of the investigated field, the potential advantageous of a geostatistical analysis becomes less. For spacing beyond the range of spatial auto-correlation, kriging estimates reduce to the same results as for the classical random sampling. A geostatistical analysis is not only computationally heavy, it also requires an impotent number of samples to be taken and analyzed as acute as possible. As mentioned before, at least 30 to 50 pairs of observations are necessary to calculate one point of the experimental variogram. Since the lag range over which the variogram is calculated should be approximately one fourth to one half of the dimension of the field studied, the experimental varogram should contain points ranging from very small to relative large lags.

Table 4. Selecting the best interpolation method according to RMSE and ME parameters

IDW					Kriging	Cokriging		GWQI
Exp 5	Exp 4	Exp 3	Exp 2	Exp 1				
0.942	0.939	0.934	0.933	0.974	**0.908**	0.975	RMSE	SAR
-0.038	-0.029	-0.013	0.01	0.029	-0.082	0.0058	ME	
1.604	1.59	1.568	1.582	1.471	1.416	**1.409**	RMSE	SO_4^{2-}
-0.5	-0.036	-0.012	0.026	0.51	-0.0703	-0.0432	ME	
702	695.3	**690**	705.2	809.5	799.2	1073	RMSE	EC
-41.41	-35.4	-23.36	-41.41	17.64	-34.83	-104. 9	ME	
6.908	6.74	**6.72**	6.809	7.975	7.564	10.67	RMSE	Cl^-
-0.425	-0.381	-0.284	-0.097	0.06	-1.147	-1.58	ME	
2.987	**2.969**	3.962	3.003	3.163	3.024	3.465	RMSE	Na^+
-0.227	-0.197	-0.136	-0.03	0.066	-0.209	-0.1968	ME	
223.8	221.7	**220.8**	228.3	272.1	266.2	377.5	RMSE	TH
-9.705	-8.172	-4.99	1.37	7.09	-2.391	-34.25	ME	

As a result, geostatistical investigation is mostly based on hundred, even thousands, of observation. If one observation of the variable is costly, this requirement many jeopardize a geostatistical analysis. Summarized, the disadvantageous of geostatistical approach toward the spatial inventory of soil variables, also called are:

1- In practice, observations need to be numerical
2- Large data sets are required
3- Storing information processing power is needed

The advantageous are

1- It is a reproducible procedure which is easy to verify and update
2- No classification of data is required. Hence all problems concerning classification disappear
3- The numerical output can serve as an input for further processing in GIS
4- It yields as conceptually much more realistic inventory than the traditional groundwater maps.

For the rest of groundwater quality indices, TH, EC, Na^+ and Cl^-, IDW technique had better result than geostatistical method to simulate groundwater quality indices. As all parameters show, demolition of groundwater is concentrated on Eastern of the region (Fig. 15-20).

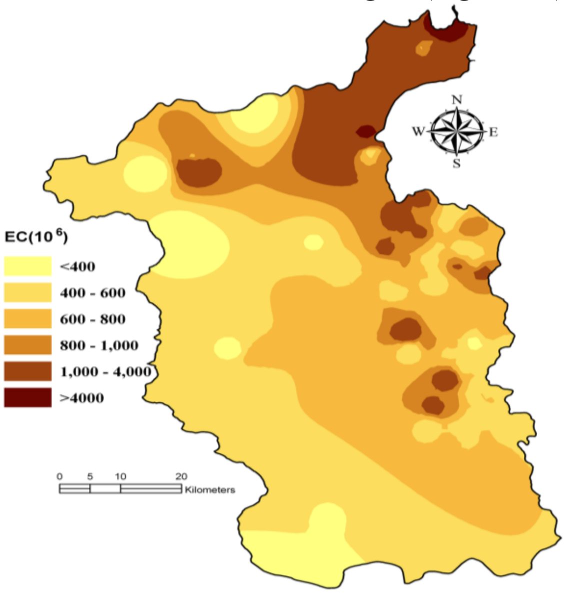

Figure 15. Interpolation Groundwater quality map based on IDW (EC)

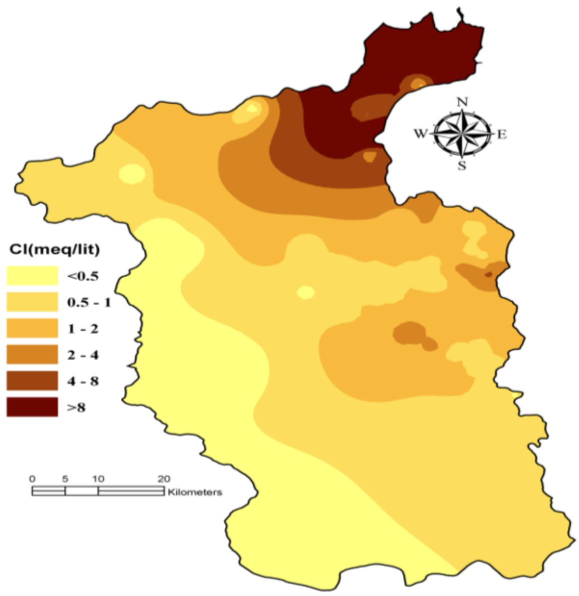

Figure 16. Interpolation Groundwater quality map based on IDW (Cl^-)

For example, EC is high in Eastern region because it is near to residential and agricultural area and these activities without considering the potential of the region along with excessive use of groundwater by other human activities intensify this process. Besides, high concentration of EC in the East of the area is related to Urmia Lake (Fig.15). This lake is the second saline lake in the word and it is obvious that higher salinity in the East of the region is related to it.

Generally, results showed that demolition of Ground water quality in Urmia plain is not very serious problem but discharging water from aquifer more than it's potential along with caring out water to adjacent cities, which has been considered in recent policies, can devastate Ground water quality in near future

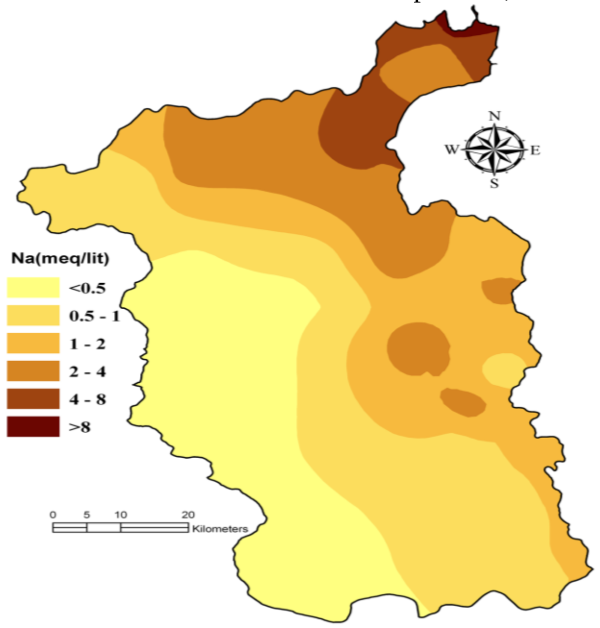

Figure 17. Interpolation Groundwater quality map based on IDW (Na^+)

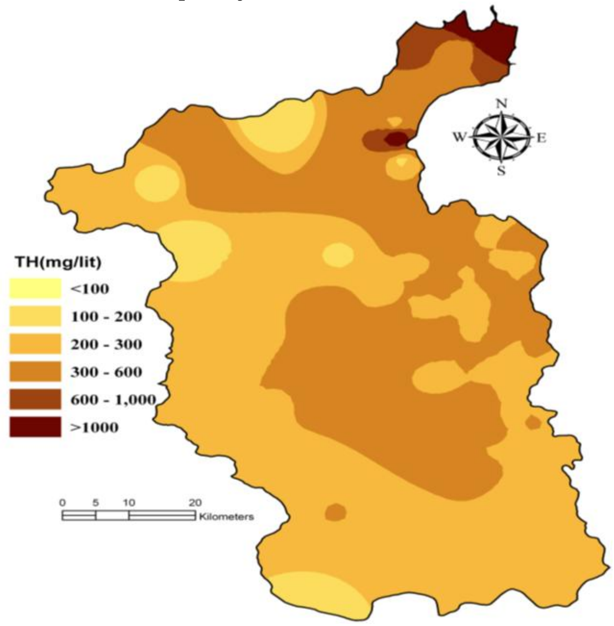

Figure 18. Interpolation Groundwater quality map based on IDW (TH)

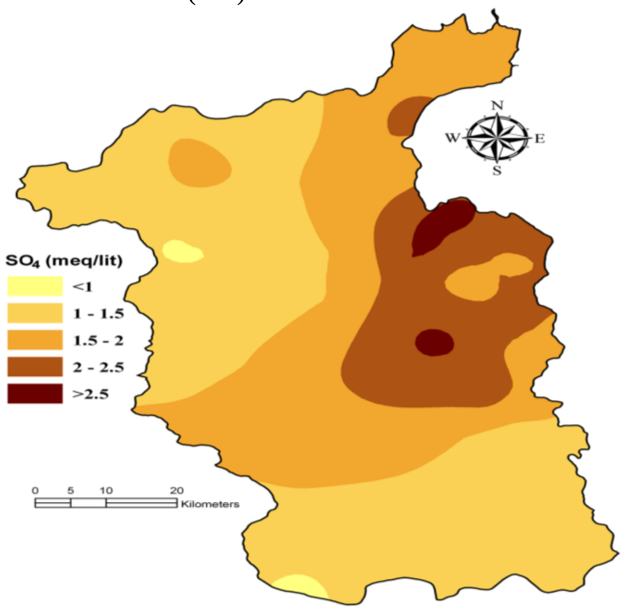

Figure 19. Interpolation Groundwater quality map based on Kriging (SO_4^{2-})

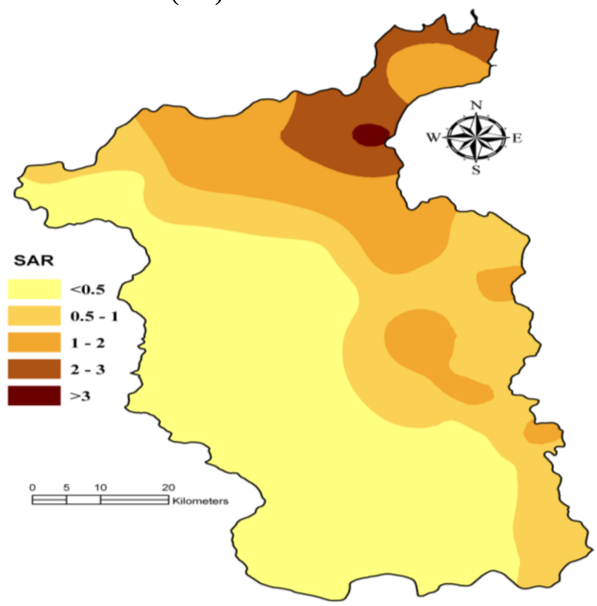

Figure 20. Interpolation Groundwater quality map based on Cokriging (SAR)

Appendix A

Na^+	Natrium
Ca^{2+}	Calcium
SO_4^{2-}	Sulphate
TH	Total Hardness
EC	Electrical Conductivity
SAR	Sodium Adsorption Ratio
Cl^-	Chlorate
GWQI	Ground Water Quality Indices
IDW	Inverse Distance Moving
RMSE	Root Mean Square Method
ME	Mean Error
GIS	Geographical Information System
RSS	Root Sum of Square

Conclusion

This study has attempted to predict the spatial distribution and uncertainty some ground water quality indices in the North Western of Iran, Urmia plain, using three interpolation techniques (Kriging, Cokriging and IDW). Since the distribution of GWQI is skewed, we transformed the values to common logarithms which reduced the skewness. The variograms and cross-variograms computed on the transformed data, and the experimental semi-variogram, were fitted best by spherical and exponential functions, using RSS. These functions were then used for the kriging and cokriging. The analysis showed that for two groundwater quality indices, So_4^{-2}, and SAR, geostatical methods performed better than IDW technique in characterizing the spatial variability, for the rest of groundwater quality indices, TH, EC, Na^+ and Cl^-, IDW had better result than geostatistical methods to simulate groundwater quality indices. This emphasize in our hypothesis that each method depends on the region, distribution of sample and other characteristics of region. It is suggested that in the future studies, other methods especially indicator and disjunctive kriging is used in order to prepare risk maps.

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